ENERGY CATALYST
Volume 2 (2026) · ISSN 3103-9952

TECHNICAL ARTICLE

Full-Curve Five-Parameter Extraction of a Commercial Photovoltaic Module Using the Single-Diode Model at Standard Test Conditions

Erdem Cuce[1,2*]

[1] Department of Mechanical Engineering, Faculty of Engineering, Istanbul Aydin University, Istanbul 34295, Türkiye
[2] University Centre for Research and Development, Chandigarh University, Mohali, Punjab 140413, India

RECEIVED 21 July 2026 · REVISED 31 August 2026 · ACCEPTED 21 September 2026 · PUBLISHED 16 October 2026

ABSTRACT

Extracting the parameters of photovoltaic (PV) modules accurately from the experimental current-voltage (I-V) curves is important for operating simulation, assessment of energy yield and degradation diagnostics. This study applies a transparent full-curve parameter-extraction method for the single-diode model (SDM) of a commercial crystalline-silicon PV module under standard test conditions (STC). The unknown parameters are the light-generated current I_{ph}, diode reverse saturation current I_0, series resistance R_s, shunt resistance R_{sh}, and modified diode ideality factor a. Unlike methods based only on short-circuit, open-circuit, and maximum-power points, the adopted procedure minimises the residuals of the implicit SDM equation over 100 measured voltage-current pairs from short circuit to open circuit. The extracted model reproduces the measured I-V and P-V characteristics with very high accuracy, with a maximum-power error of only 0.009% and an R^2 value of 0.99999996. These results demonstrate the high numerical accuracy of the full-curve fitting procedure without relying on module-specific voltage, current, or power values. The results obtained confirm that it is possible to obtain full-curve residual fit capable of describing the experimental I-V and P-V characteristics with a very high precision. Simultaneously, the article highlights the importance of understanding the remarkable numerical consistency of the parameter identifiability and measurement resolution concerning cases when the experimental curve is either rounded or approximates the ideal one before reaching the knee point.

KEYWORDS photovoltaic module, single-diode model, five-parameter extraction, I-V curve, nonlinear least squares, STC, model efficacy, parameter identifiability

Nomenclature

Symbol	Description	Unit
a	Modified diode ideality factor of the module	V
FF	Fill factor	-
I	PV module output current	A
I_0	Diode reverse saturation current	A
I_{mp}	Current at maximum power point	A
I_{ph}	Light-generated or photocurrent	A
I_{sc}	Short-circuit current	A
k	Boltzmann constant	$\frac{J}{K}$
n	Effective diode ideality factor	-
N_s	Equivalent number of series-connected cells	-
P_{max}	Maximum power	W

* Corresponding author. Email address: erdemcuce@aydin.edu.tr (Erdem Cuce)

© 2026 The Author(s).
Published by Caravel Press.

doi.org/10.65582/ec.2026.011

(continued)

Symbol	Description	Unit
q	Elementary charge	C
R_s	Series resistance	Ω
R_{sh}	Shunt resistance	Ω
T	Cell temperature	K
V	PV module output voltage	V
V_{mp}	Voltage at maximum power point	V
V_{oc}	Open-circuit voltage	V
V_T	Thermal voltage of one cell	V

1. Introduction

The Photovoltaic (PV) energy sector began as an alternative renewable sector, but nowadays it is one of the most significant sectors of green energy. Thanks to its modular construction the technology can be applied in various ways, including residential rooftops, commercial buildings, grid-scale solar parks, airport installations, agricultural facilities, hybrid renewable systems, and building-integrated photovoltaic-thermal (BIPVT) systems. As PV penetration increases, the need for accurate, transparent, and repeatable electrical models is growing. Such models are essential not only for nominal power rating but also for energy efficiency estimation, inverter sizing, maximum power point tracking (MPPT), digital twin development, fault diagnosis, degradation monitoring, and technical-economic evaluation.

The electrical behaviour of a PV module is most directly represented by its current-voltage (I-V) and power-voltage (P-V) characteristics. These curves contain the main performance indicators of a module: short-circuit current (I_{sc}), open-circuit voltage (V_{oc}), maximum-power voltage (V_{mpp}), maximum-power current (I_{mpp}), maximum power (P_{mpp}), and fill factor (FF). Even if these indicators seem easy to understand and use, they are influenced by the combination of a number of factors, including photogeneration processes, the recombination of charge carriers in the cell, the ohmic losses, the leakage current flowing through the module, the temperature, the light conditions, the corresponding spectrum, the type of PV module technology used, and also the type of encapsulation. As a result, an approach that only models the rated maximum output power is not enough, as it is crucial that the entire curve shape is modelled accurately for the proposed model to be useful for simulation and diagnostics.

Environmental sensitivity is a significant issue in photovoltaic (PV) modelling. Cuce and Bali (2009) have shown that the characteristics of a polycrystalline silicon PV module are influenced by the intensity of solar irradiation as well as the temperature of the module. Based on this, it is clear that the electrical parameters cannot be considered fixed constants due to the changeability of the conditions. The work by Cuce et al. (2017) is of special importance because it represents a highly accurate model of a PV module for the prediction of electrical properties as well as thermodynamic performance characteristics.

Accurate PV modelling is practically important because of its influence on every facet of PV technology. PV modelling can be used in hybrid PV-solar-wind systems for power balance calculations, sizing of storage systems, reliability assessment, and control strategy selection (Soudagar *et al.* 2024). In airports, consideration needs to be given not just to the achieved energy output, but to possible glare and safety of operations (Sreenath *et al.* 2020). In the tropical monsoon region dominated by rain, utility-scale PV (polycrystalline) plant efficiency depends on the clouds, moisture, diffuse radiation, and meteorological conditions of the site (Gopi *et al.* 2021). Similar to this, BIPVT (Building-integrated Photovoltaic-Thermal) systems and spectral splitting technologies have to combine optical and thermal models (Ma *et al.* 2024). Another growing area in PV technology is the

study of PV cooling technology implemented in high-temperature conditions aimed at reducing thermal losses in PV modules and possibly improving their output efficiency (Abdirahman *et al.* 2025). In all these cases, the need for an accurate electrical sub-model of PV drives the careful PV model optimisation based on I-V data of PV performance.

The use of equivalent circuit models is now firmed as the most popular way to model the electrical behaviour of PV systems as it relates the characteristics of the observable curves to parameters that have physical interpretation. Among these models, the single-diode model (SDM) is the most widely used of the models since it achieves a reasonable trade-off among complexity, clarity and computational expense. The five-parameter SDM consists of light-generated current, current through the reverse-biased diode, series resistance, shunt resistance and modified ideality factor of the diode. These parameters are responsible for the value of the current plateau, the shape of the exponential part of the voltage-current curve (V-I curve), making its power drop and influencing the shape of the I-V curve knee. The same modelling approach is applied in other common PV modelling tools and software like PVPMC, PVsyst and pvlib-python (Tamrakar and Sawle 2015; Mermoud and Lejeune 2010; Holmgren *et al.* 2018).

Complex equivalence circuit models, such as double and triple diodes, can account for processes that are not involved in the above models. However, increasing the details about the physical process causes more unknowns in the model, higher calculation complexity, more correlations between parameters, and significant chances of obtaining multiple solutions. In contrast, the low number of parameters in the five-parameter single diode model makes it a reasonable option for correctly conducting the curve reconstruction and practical engineering. The importance of standard testing conditions is that they provide the context of controlled testing conditions against measured and modelled performance of solar panels, knowing that the outdoor application will need to be adjusted based on the irradiance and temperature models (Carrillo *et al.* 2017; De Soto *et al.* 2006). Nevertheless, even with the standard test conditions taken into consideration, the PV curves will still suffer from data resolution, measurement errors, smoothing of the curve, and representation of the voltage-current data. Therefore, the extraction procedure should not be evaluated only by its final numerical error; it should also be examined in terms of how the residuals are constructed, how the entire curve is used, and whether the resulting parameters remain physically interpretable. This consideration is especially relevant for commercial modules whose measured I-V data may appear nearly ideal over a large part of the operating range (Villalva *et al.* 2009; Batzelis and Papathanassiou 2016; Lineykin *et al.* 2014).

Reliability of the single-diode model largely depends on the method used to estimate its parameters. Traditional analytical approach and characteristic-methods use such measurements as I_{sc}, V_{oc}, V_{mpp}, I_{mpp}, FF, local slopes, and temperature coefficients to assess the unknown values (Jain 2004; Cubas *et al.* 2014). Lambert W formulae and direct analytical transformations have been created in order to facilitate calculations. Numerical procedures, including Newton-Raphson and nonlinear least-squares methods solve original equations directly and are promising, as they allow to define residuals, limitations, and process of convergence (Qin *et al.* 2024; Gu *et al.* 2023). Recently, metaheuristic and hybrid optimisation methods have started to be used in the area in question as they allow conducting searches in complicated and non-convex spaces with minimal usage of derivatives (Izci *et al.* 2024; Abbassi *et al.* 2018; Li *et al.* 2021; Younis *et al.* 2022; Song *et al.* 2021; Abdulrazzaq *et al.* 2025; Nunes *et al.* 2018). Each approach described poses its own benefits as well as limitations related to assumptions, sensitivity to initial values, calculation requirements, stochastic variation, or incomplete usage of measured curve data.

The advantage of the full-curve fitting approach is in that it accounts for the entire information encompassed in the recorded I-V characteristics and does not rely on data from selected points. Characteristic-point methods can obtain reasonably accurate predictions of the short-circuit current, open-circuit voltage, and maximum power, but they may not reconstruct the curve properly between these regions of operation. The purpose of the distinction is that making any efforts to derive

complexities that depend on irradiance or temperature from just one dataset is not the case here. The difference is essential for outdoor predictions since they would require additional equations for different temperatures and irradiances and multi-condition testing (Qin *et al.* 2024; Gu *et al.* 2023; Younis *et al.* 2022).

Full-curve parameter fitting is not new in PV modelling and has been used in previous studies to estimate SDM parameters from measured I-V data. Least-squares and nonlinear optimisation methods have been applied to fit the model over the measured operating range, while more recent deterministic and hybrid approaches have also been evaluated using complete I-V datasets (Abdulrazzaq *et al.* 2022). A recent review by Deotti and da Silva Junior (2023) further shows that parameter extraction from measured I-V curves has been widely formulated as an optimisation problem in which the model is fitted to the available experimental points. Therefore, the present study does not claim novelty in the use of full-curve fitting itself. Instead, it focuses on a transparent and reproducible implementation of residual-based SDM fitting for a commercial PV module, together with full-curve validation and a discussion of parameter plausibility and identifiability.

Recent PV modelling studies have also extended parameter estimation beyond conventional deterministic and metaheuristic extraction. Uncertainty-aware approaches have increasingly emphasised parameter sensitivity and the reliability of individual SDM estimates rather than relying only on a single fitting-error value (Xu *et al.* 2025). Machine-learning methods have also been investigated for predicting SDM parameters across different modules and operating conditions (Inbamani and Prabha 2023). More broadly, physics-informed and hybrid physics–machine-learning approaches are being explored to combine physical consistency with the flexibility of data-driven models (Santos *et al.* 2024). These developments are also relevant to emerging digital-twin applications in PV systems, where physically interpretable models and continuously updated operational data can support monitoring, prediction, and diagnostics (Angelova *et al.* 2024).

A major issue reported in the literature is that great fit data is sometimes presented without elaborating on how the residuals have been calculated, which data points have been used, and whether the parameters found are reasonable. More importantly, a small root-mean-square error (RMSE) does not necessarily imply that all five parameters of the SDM are independently identifiable. This is governed by multiple coupling between the various parameters: the reverse saturation current and the ideality factors influence the exponential knee, while series and shunt resistances determine the slopes, which may be weakly visible on the measured curve if it is rounded or almost ideal. This is why discussions on PV model metrics and parameter estimation state that accuracy metrics should be put in conjunction with the structure of the model itself, measuring accuracy, and plausibility of the parameters (Abdulrazzaq *et al.* 2025; Nunes *et al.* 2018; Ćalasan *et al.* 2020; Gnetchejo *et al.* 2019).

This study addresses the aforementioned issues by applying an explicit full-curve five-parameter extraction process to a commercial crystalline-silicon PV module tested under STC. The suggested approach not only takes into account key characteristic points but also uses 100 voltage-current measurements in the entire range from short circuit to open circuit. The SDM has been written in residual form, and the method of constrained nonlinear least squares has been employed. In addition to this, the developed model has been verified through the reproduction of the characteristics, evaluation of the predicted maximum power, calculation of the indicators of the error of the full curve, and analysis of the parameters' plausibility.

In this context, the current study does not aim to present a new optimisation algorithm nor engage in competition with the major metaheuristics benchmarks. Its important contribution lies in giving an example of a transparent and reproducible extraction approach for a measured commercial PV module characteristic. The focus of the present study is a transparent implementation in which the implicit SDM is expressed in residual form and all measured voltage-current pairs are fitted simultaneously, providing a direct link between the measured data, the extracted parameter set, and the reconstructed I-V and P-V curves. The analysis makes the method performable, repeatable, and

flexible enough for other experimental PV datasets. Thus, the contribution of the study is the following. First of all, it provides a reproducible procedure of fitting based on the residuals that can be applied directly to the measured PV modules, including the curves. Secondly, it shows that although the full-curve fitting can perfectly reproduce the measured I-V and P-V characteristics, it avoids the problems of characteristic point only extraction. Finally, it emphasises the importance of not confounding perfectly fitted curves with the physical identifiability of all the parameters. Accordingly, the distinction of the present study does not lie in introducing a new optimisation algorithm, but in combining pointwise residual formulation, physically constrained parameters, open-circuit-based initialisation, logarithmic treatment of numerically sensitive parameters, and parameter-plausibility assessment within a single reproducible workflow. No claim is made that the present formulation provides superior convergence or computational performance compared with previously reported full-curve methods.

2. Material and Methods

2.1. Measured I-V Curve and STC Basis

The input dataset consists of 100 voltage-current pairs measured from the short-circuit region to the open-circuit region of a commercial crystalline-silicon PV module. The dataset represents one operating condition at STC. Accordingly, the present validation should be interpreted as a single-condition demonstration rather than as evidence of robustness across different PV modules or operating conditions. In PV testing, STC conventionally corresponds to 1000 W/m² irradiance, 25 $^{\circ}C$ cell temperature, and the AM1.5 reference spectrum. Therefore, the extracted parameters should be interpreted as reference-condition parameters rather than as complete outdoor parameters. Because only one I-V curve is used, the extraction problem is deliberately constrained to the reproduction of the measured STC curve. No effort is made to derive complete parameter functions dependent on irradiance or temperature from only this one dataset. This distinction is essential since outdoor forecasting is based on the need for further temperature and irradiance translation equations and multi-case validation. The present study does not involve an independent experimental measurement campaign; rather, it focuses on parameter extraction from an available STC I–V dataset. Detailed information on the original measurement instrumentation, calibration procedure, measurement uncertainty, and repeatability was not available for the present analysis.

The main electrical characteristics obtained directly from the measured I–V and P–V curves are summarised in Table 1.

Table 1. Main electrical characteristics obtained from the measured I–V curve at STC

Parameter	Symbol	Value
Short-circuit current	I_{sc}	9.3 A
Open-circuit voltage	V_{oc}	39.500 V
Maximum-power voltage	V_{mp}	33.116 V
Maximum-power current	I_{mp}	8.653 A
Maximum power	$P_{\max}$	286.553 W

The electrical power at each measured point is calculated as:

$$P_i = V_i I_i \tag{1}$$

The fill factor is calculated as:

$$FF = \frac{P_{\max}}{V_{oc} I_{sc}} = \frac{286.553}{39.50 \times 9.30} = 0.7801 \tag{2}$$

Thus, the supplied curve corresponds to an approximately 286.6 W PV module at STC.

2.2. Equivalent-Circuit Model Selection

The choice of the five-parameter SDM model can be justified since it is a compact model with a meaningful physical interpretation of the model curve. Unlike the ideal current-source model, the SDM incorporates diode behaviour together with series-resistance losses and shunt-leakage effects. And unlike the double-diodes or triple-diodes cascade models, this one does not have any additional variables which cannot be classified using only one curve without additional assumptions.

The model divides the electrical current into three theoretical elements: current produced by light, diode current, and current through leakage. This structure allows the fitted parameter set to be interpreted in relation to the shape of the I-V curve: I_{ph} fixes the current plateau, I_0 and a control the exponential knee, R_s influences the high-voltage slope and fill factor, and R_{sh} influences the low-voltage slope and leakage behaviour.

2.3. Governing Single-Diode Equation

The five-parameter single-diode model is expressed as:

$$I = I_{ph} - I_0 \left[\exp\left(\frac{V + IR_s}{a} \right) - 1 \right] - \frac{V + IR_s}{R_{sh}} \tag{3}$$

where I is the module current, V is the module voltage, I_{ph} is the photocurrent, I_0 is the diode reverse saturation current, R_s is the series resistance, R_{sh} is the shunt resistance, and a is the modified diode ideality factor. The modified ideality factor is:

$$a = nN_s V_T \tag{4}$$

Here, a is a module-level modified diode ideality parameter expressed in volts, incorporating the effective diode ideality factor n, the equivalent number of series-connected cells N_s, and the cell thermal voltage V_T.

The thermal voltage is:

$$V_T = \frac{kT_c}{q} \tag{5}$$

At STC, $T_c = 298.15$ K and the thermal voltage of one cell is VT=0.0256926 V
Using $k = 1.380649 \times 10^{-23}$ J/K and $q = 1.602176634 \times 10^{-19}$ C;
For a 60-cell equivalent crystalline-silicon module:

$$N_s V_T = 60 \times 0.0256926 = 1.54155\ V \tag{6}$$

After extraction, the effective diode ideality factor is recovered from:

$$n = \frac{a}{N_s V_T} \tag{7}$$

2.4. Physical Role of the Five Parameters

Each parameter of the five-parameter single-diode model has a distinct physical meaning and affects a specific region of the I-V curve. The photocurrent I_{ph} mainly determines the current level near the short-circuit condition and is therefore closely associated with the incident irradiance. The diode reverse saturation current I_0 governs the exponential current loss and has a strong influence on the open-circuit region. The modified diode ideality factor a, or equivalently the ideality factor n, controls the curvature and sharpness of the knee region. The series resistance R_s is an indicator of losses in the cells, contacts, interconnects, and wires. Increasing R_s lowers the fill factor. The resistance R_{sh} compared to shunt currents describes the leakages in the junction or the whole module. A low value of R_{sh} allows more shunt current to move through the solar cell, resulting in worse stability of the low-voltage plateau. The physical interpretation, main curve influence, and practical implication of each SDM parameter are summarised in Table 2.

Table 2. Physical meaning and curve influence of the five SDM parameters.

Parameter	Physical interpretation	Main curve influence	Practical implication
I_{ph}	Light-generated current	Current level near I_{sc}	Irradiance response and current scaling
I_0	Diode reverse saturation current	Exponential fall near V_{oc}	Recombination/loss behaviour
R_s	Ohmic resistance of cells, contacts, interconnects, and wiring	Slope and power loss near high voltage	Fill-factor and power reduction
R_{sh}	Leakage resistance across the junction/ module	Slope near short circuit	Leakage, defects, and low-light behaviour
a or n	Effective diode ideality behaviour	Knee curvature	Diode quality and curve sharpness

2.5. Overview of Parameter Extraction Approaches

PV parameter extraction methods can be divided into five distinct classifications based on the type of input data, solving strategy, and curve information level included in the extraction process. Characteristic-point analytical methods use datasheet or measured values such as I_{sc}, V_{oc}, MPP, and temperature coefficients. These methods are fast and easy to implement, but they usually require simplifying assumptions and may not reproduce the complete I-V curve accurately. Analytical slope techniques utilise local derivatives in the near vicinity of open circuit and short circuit situations in order to calculate resistance parameters. Despite the intuitive nature of these techniques, the validity of their results may vary greatly depending on environmental noise, smoothing of the curve, and digitisation errors. Numerical deterministic methods can be used to solve nonlinear equations or to directly minimise the residual of the function. They may yield correct results provided that the initial guesses, limits, and convergence criteria are appropriately selected. Metaheuristic methods search the parameter space using population-based or nature-inspired optimisation algorithms and can handle non-convex objective functions, but they often require many function evaluations and careful adjustment of algorithmic control parameters. Hybrid methods combine analytical initialisation with numerical or metaheuristic refinement in order to improve convergence and robustness. The main features, advantages, limitations, and suitability of these approaches for the present work are summarised in Table 3.

Table 3. Main approaches for five-parameter PV model extraction.

Approach	Typical input	Advantages	Limitations	Suitability for the present work	Ref
Datasheet analytical	I_{sc}, V_{oc}, V_{mp}, I_{mp}, temperature coefficients	Fast; simple; useful when raw I-V data are unavailable	Needs assumptions; may not match full curve	Not preferred because full I-V data are available	Batzelis and Papathanassiou (2016); Cubas et al. (2014)
Slope-based analytical	Characteristic points plus local slopes	Gives direct resistance estimates	Very sensitive to noisy or rounded slopes	Useful for interpretation, not final fitting	Xu et al. (2023)
Newton/ nonlinear equations	Characteristic equations	Deterministic and fast near solution	May depend on initial guesses; local convergence	Useful but uses limited curve information	Abbassi et al. (2018)
Full-curve least squares	Complete the measured I-V curve	Uses all data; strong curve fidelity; transparent residuals	Parameters can be correlated; requires bounds	Selected method	Xu et al. (2023); Abdulrazzaq et al. (2022)
Metaheuristic / hybrid	Complete curve or benchmark datasets	Less dependent on derivatives; handles non-convex spaces	More computational effort; stochastic variability	Useful comparator, but unnecessary for this smooth curve	Lidaighbi et al. (2022); Qin et al. (2024); Gu et al. (2023); Li et al. (2021); Nunes et al. (2018)

The computational effort reported in Table 3 is expressed qualitatively because absolute execution time depends strongly on the implementation, hardware, dataset size, stopping criteria, and initialisation strategy. Analytical approaches generally require the least computational effort, whereas deterministic full-curve least-squares fitting requires repeated residual evaluation over all measured points. Metaheuristic and hybrid approaches typically involve a larger number of objective-function evaluations and therefore require greater computational effort.

The method used in the present study belongs to the full-curve deterministic least-squares family. It is selected because the available dataset contains the complete measured I-V curve and because the objective of this study is to obtain a transparent, reproducible, and physically interpretable parameter set rather than to benchmark stochastic optimisation algorithms.

2.6. Residual Formulation for Full-Curve Fitting

The implicit single-diode model was rearranged into residual form. The diode and shunt current terms are defined as:

$$I_{D,i} = I_0\left[\exp\left(\frac{(V_i + I_i R_s)}{a}\right) - 1\right] \tag{8}$$

$$I_{sh,i} = \frac{(V_i + I_i R_s)}{R_{sh}} \tag{9}$$

The residual at each measured point is:

$$F(V_{i,}I_i) = I_i - I_{ph} + I_{D,i} + I_{sh,i} \tag{10}$$

For an exact model, $F(V_i, I_i) = 0$ for all measured points. The parameter vector is:

$$\theta = \left[I_{ph},\ I_0,\ R_s,\ R_{sh},\ a\right] \tag{11}$$

The optimisation problem is:

$$\theta^* = \underset{\theta}{argmin} \sum_{i=1}^{N} F(V_i,\ I_i)^2 \tag{12}$$

This formulation fits the implicit model directly to the measured voltage-current pairs. Because all 100 data points are used, the extracted parameter set is constrained by the low-voltage plateau, knee region, and open-circuit side simultaneously.

2.7. Numerical Implementation and Initialisation

The nonlinear least-squares problem is solved using physically constrained parameters. The initial values used in the optimisation are summarised in Table 4.

Table 4. Initial parameter values used in the optimisation

Parameter	Initial Value
$I_{ph}^{(0)}$	9.30 A
$a^{(0)}$	1.60 V
$R_s^{(0)}$	0.20Ω
$R_{sh}^{(0)}$	5000Ω

The initial diode saturation current is estimated from the open-circuit condition:

$$I_0^{(0)} = \frac{I_{ph}^{(0)} - V_{oc}/R_{sh}^{(0)}}{exp(V_{oc}/a^{(0)} - 1} \tag{13}$$

Using the values given in Table 4, the initial diode saturation current is calculated as $I_0^{(0)} = 1.764 \times 10^{-10} A$

To improve numerical conditioning, I_0, R_s, and R_{sh} are handled in logarithmic form during optimisation. This prevents negative resistance or saturation-current values and improves convergence because these parameters can span several orders of magnitude.

The overall parameter-extraction procedure and the sequence in which the governing equations are applied are summarised in Figure 1.

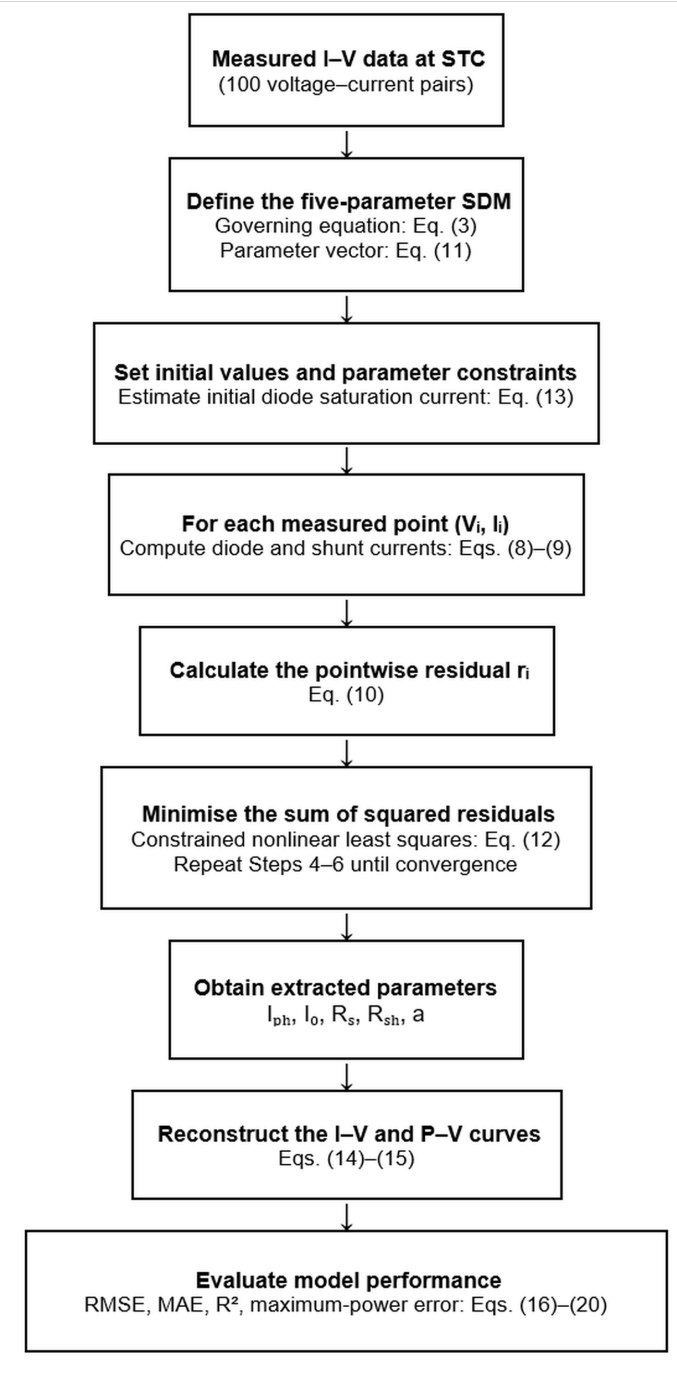

Figure 1. Flowchart of the full-curve five-parameter SDM parameter-extraction procedure

2.8. Reconstruction of the I-V Curves

After the parameters are extracted, the model current at any imposed voltage is obtained by solving the implicit equation:

$$g(I;\, V) = I - I_{ph} + I_D + I_{sh} = 0 \tag{14}$$

where I_D and I_{sh} follow Equations (8) and (9) for the selected voltage value.
The power curve is then reconstructed from:

$$P(V) = VI(V) \tag{15}$$

The model maximum-power point is identified by maximising $P(V)$ over the interval $0 \le V \le V_{oc}$.

2.9. Model-Efficacy Indicators

The efficacy of the extracted model is assessed using both characteristic-point and full-curve indicators. The pointwise current error is defined as:

$$e_i = I_{m,i} - I_{fit,i} \tag{16}$$

The root-mean-square error is:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(I_{m,i} - I_{fit,i}\right)^2} \tag{17}$$

The mean absolute error is:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|I_{m,i} - I_{fit,i}\right| \tag{18}$$

The coefficient of determination is:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(I_{m,i} - I_{fit,i}\right)^2}{\sum_{i=1}^{N}\left(I_{m,i} - \bar{I}_m\right)^2} \tag{19}$$

The maximum-power error is:

$$\varepsilon_{P_{\max}} = \frac{P_{\max,fit} - P_{\max,m}}{P_{\max,m}} \times 100 \tag{20}$$

The specified metrics were chosen because of the fact that RMSE punishes more for bigger deviations, MAE allows calculating average absolute current error in an easy manner, R^2 represents global similarity of the curve, while maximum power error shows how relevant the model is for energy and MPPT issues.

3. Results and discussion

3.1. Extracted Five-Parameter Set

The received parameter set is summarised in Table 5. It is shown that the obtained solution is able to mimic the experimental curve with a very small number of residuals for the entire range of the voltage.

Table 5. Extracted five-parameter single-diode model values.

Parameter	Symbol	Extracted value
Photocurrent	I_{ph}	9.299890 A
Diode reverse saturation current	I_0	6.3407e-07 A
Series resistance	R_s	1.4682e-04 ohm

Table 5. (continued)

Parameter	Symbol	Extracted value
Shunt resistance	R_{sh}	1.3029e+06 ohm
Modified ideality factor	a	2.393781 V
Ideality factor, assuming $N_s = 60$	n	1.5528

The diode ideality factor was calculated as:

$$n = \frac{a}{N_s V_T} = \frac{2.393781}{60 \times 0.0256926} = 1.5528 \tag{21}$$

The equation of the fitted model is given by Equation (3) based on the values in Table 5. To avoid a lengthy equation, the fitted current balance is divided into three components:

$$I = 9.299890 - I_D - I_{sh} \tag{22}$$

$$x = V + 1.4682 \times 10^{-4} I \tag{23}$$

$$I_D = 6.3407 \times 10^{-7} \left[\exp\left(\frac{x}{2.393781} \right) - 1 \right] \tag{24}$$

$$I_{sh} = \frac{x}{1.3029 \times 10^{6}} \tag{25}$$

3.2. Characteristic-Point Reproduction

The newly extracted model shows the characteristics of the measured I-V curve quite effectively in terms of important points, as demonstrated in Table 6.

Table 6. Comparison between measured and modelled characteristic points.

Quantity	Measured value	Modelled value	Error
I_{sc}	9.300 A	9.29989 A	-0.00011 A
V_{oc}	39.500 V	39.50001 V	+0.00001 V
V_{mp}	33.116 V	33.048 V	-0.068 V
I_{mp}	8.653 A	8.672 A	+0.019 A
$P_{\max}$	286.553 W	286.579 W	+0.026 W

The percentage error in maximum power is:

$$\varepsilon_{P_{\max}} = \frac{286.579 - 286.553}{286.553} \times 100 = 0.009\% \tag{26}$$

The model also satisfies the maximum-power-point slope condition. At the fitted MPP:

$$\frac{dI}{dV} = -0.262401\ A/V \tag{27}$$

$$-\frac{I_{mp}}{V_{mp}} = -\frac{8.672}{33.048} = -0.262401\ A/V \tag{28}$$

The maximum-power error is quite insignificant at 0.009%, which indicates that the model has managed to maintain the actual power characteristics of the measured curve. Moreover, the small difference in voltage and current at MPP is negligible, since some variations of the V_{mp} and I_{mp} have hardly any influence on the peak maximum power on the P-V curve.

3.3. Full-Curve Fitting Accuracy

The goodness of fit of the extracted single-diode model is studied by comparing the calculated current values to the experimental ones for the entire region of analysed voltage values from short circuit to open circuit. This is important because the model may show satisfactory correlation with such points like I_{sc}, V_{oc}, or maximum power point, but provide noticeable discrepancies at other points.

The statistical error indicators obtained from the full-curve comparison are presented in Table 7. The root-mean-square error is only 3.15×10^{-4} A, while the mean absolute error is 2.53×10^{-4} A. These values are extremely small compared with the module current level of approximately 9.3 A, indicating that the reconstructed curve follows the measured curve with very high precision. The maximum absolute current error is 7.87×10^{-4} A, which confirms that even the largest pointwise deviation remains below one milliampere. In addition, the coefficient of determination was R^2=0.99999996, showing an almost perfect agreement between the measured and modelled current values.

Table 7. Full-curve fitting accuracy

Indicator	Value
RMSE	$3.15 \times 10^{-4} A$
MAE	$2.53 \times 10^{-4} A$
Maximum absolute current error	$7.87 \times 10^{-4} A$
R^2	0.99999996

To clarify the relationship between the curves both measured and calculated, corresponding values of voltage and current have been checked and presented in Table 8. Chosen points were distributed in such a way as to cover the low voltage current plateau, the knee region, the high power region, and the reverse current area of the characteristic. For V=0 V, the model shows 9.29989 A as compared to 9.300 A short circuit current. In the high power range case, for instance, at V=33.116 V, the measured current equals 8.653 A while the one predicted by the model is equal to 8.65350 A. Near the open circuit at V=39.500 V, the model current is only 0.00006 A, which is practically equal to zero and, hence, corresponds to the measured open circuit condition.

Table 8. Representative measured-model comparison.

Voltage (V)	Measured current (A)	Modelled current (A)	Model - measured (A)
0.000	9.300	9.29989	-0.00011
20.348	9.297	9.29676	-0.00024
29.924	9.129	9.12950	+0.00050
33.116	8.653	8.65350	+0.00050
35.111	7.812	7.81255	+0.00055
37.106	5.878	5.87774	-0.00026

Table 8. (continued)

Voltage (V)	Measured current (A)	Modelled current (A)	Model - measured (A)
38.702	2.636	2.63539	-0.00061
39.500	0.000	0.00006	+0.00006

The representative errors in Table 8 show that the deviations are small and randomly distributed around zero, rather than being concentrated in a particular voltage region. This behaviour indicates that the extracted parameter set does not only force agreement at a few selected points but also preserves the overall shape of the measured I-V curve. The current plateau at low voltage, the transition through the knee region, and the rapid current decrease near open circuit are all accurately reproduced.

The graphical comparison in Figure 2 further confirms this agreement. The fitted I-V curve almost overlaps the measured curve across the entire operating range, demonstrating that the full-curve least-squares formulation successfully captures the electrical behaviour of the commercial PV module at STC.

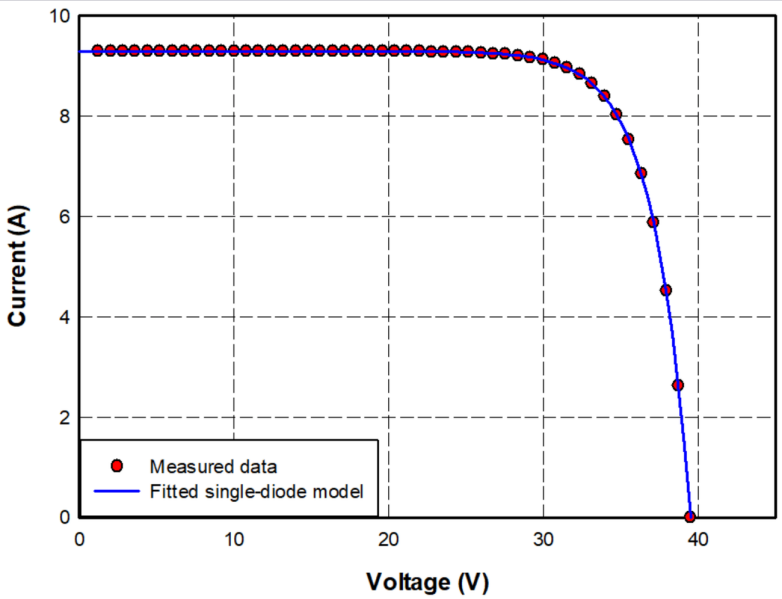

Figure 2. Measured and fitted I-V curve of the PV module at STC.

Similarly, Figure 3 shows that the reconstructed P-V curve follows the measured power curve closely and reproduces the maximum-power region with negligible deviation. This is particularly important because the accuracy of the P-V curve directly affects maximum-power prediction, MPPT studies, and energy-yield simulations.

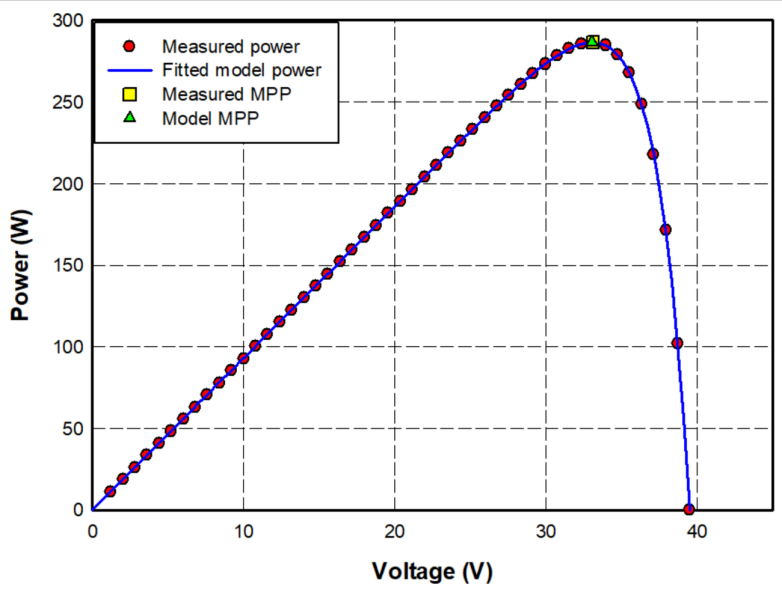

Figure 3. Measured and fitted P-V curve of the PV module at STC.

Overall, the full-curve accuracy indicators, the representative pointwise comparison, and the graphical agreement demonstrate that the extracted five-parameter single-diode model provides a highly accurate reconstruction of the measured PV module behaviour. The very low RMSE and MAE values confirm the numerical efficacy of the fitting procedure, while the near-unity R^2 value shows that almost all variation in the measured current data is explained by the reconstructed model. These findings support the suitability of the proposed full-curve residual-based extraction method for accurate PV module modelling under STC.

3.4. Comparison with extraction approaches and model efficacy

The fitting results presented in Section 3.3 establish the numerical accuracy of the extracted model and provide the basis for the following methodological comparison. Compared with datasheet-based analytical methods, the present approach uses richer experimental information because it includes all measured voltage-current pairs in the objective function. Datasheet and characteristic-point methods are useful when raw I-V data are unavailable, but they usually rely on simplifying assumptions and may not reproduce the intermediate regions of the curve accurately. In particular, a method that matches only I_{sc}, V_{oc}, and the maximum-power point can still produce deviations in the plateau, knee, or open-circuit regions. The present full-curve approach reduces this weakness by distributing the fitting requirement over the entire measured curve. Slope-based methods provide a physically intuitive approach to estimating resistance terms by using local derivatives near the short-circuit and open-circuit regions. However, these methods are highly sensitive to curve smoothing, measurement noise, data resolution, and rounding. This is especially important for the present dataset because the low-voltage current plateau is nearly horizontal and the measured current values are rounded. Under such conditions, local slopes may be weakly observable, and direct slope-based resistance extraction can yield unstable estimates. The residual-based fitting method is therefore more appropriate because it does not depend only on a small number of local derivative values. Compared with Lambert W-based analytical formulations and explicit rearrangements, the present formulation keeps the implicit SDM structure and directly minimises the current-balance residuals. Lambert W approaches are mathematically useful and can improve analytical tractability, but the full-curve residual formulation is easier to connect with measured experimental data because each measured voltage-current pair contributes directly to the optimisation problem. This makes the procedure transparent and easy to audit. Metaheuristic and hybrid optimisation algorithms have

been widely used for PV parameter extraction because they can search complex and non-convex parameter spaces with fewer derivative requirements. These methods are particularly valuable when multiple I-V curves, degraded modules, partial shading conditions, or highly nonlinear objective functions are involved. However, they may require many function evaluations and exhibit stochastic variability across runs. In the present study, the measured curve is smooth, single-condition, and well-behaved; therefore, a physically constrained deterministic least-squares method provides excellent accuracy without the additional complexity of population-based optimisation. The aim of the present work is therefore not to claim that deterministic least-squares fitting is universally superior to all metaheuristic or hybrid techniques. Rather, the results show that when a complete, smooth I-V curve is available, a transparent full-curve residual formulation can provide an accurate, reproducible, and computationally efficient parameter-extraction route. This makes the method suitable for practical PV module modelling, MPPT studies, reference-curve generation, and simulation-based performance assessment.

3.5. Parameter identifiability, limitations, and practical implications

Although the fitted model reproduces the measured curve with very high numerical accuracy, the extracted parameters should be interpreted with appropriate caution. In the five-parameter single-diode model, several parameters influence overlapping regions of the I-V curve. For example, the diode reverse saturation current and the modified ideality factor a jointly control the exponential behaviour near the knee and open-circuit regions, while the series resistance and shunt resistance influence curve slopes that may be weakly visible in a smooth or rounded dataset. Therefore, a very low fitting error does not automatically mean that every parameter has been independently and uniquely identified. A formal quantitative identifiability analysis, including confidence intervals, parameter-correlation assessment, and multi-start tests with different initial conditions, was not performed in the present study and is therefore not claimed. Such analyses are considered an important extension of the present work, particularly when multi-condition I–V data and measurement-uncertainty information are available. This issue is particularly relevant for the present module curve. The extracted photocurrent I_{ph}=9.299890 A is physically consistent with the measured short-circuit current of 9.300 A, confirming that the low-voltage current plateau is well represented. Similarly, the extracted I_0, a, and effective ideality factor n=1.5528 reproduce the knee and open-circuit behaviour successfully. However, the very low series resistance R_s=1.4682×10^{-4} Ω and very high shunt resistance I_{sh}=1.3029×10^{6} Ω should be regarded as effective fitted parameters rather than direct physical measurements of contact resistance or leakage resistance. The reason is that the measured I-V curve remains almost flat over a wide voltage interval and then decreases sharply near the knee region. Such a curve shape mathematically favours a very small R_s and a very large R_{sh}, especially when the current values are rounded. This does not diminish the model's usefulness for curve reconstruction, as the reconstructed I-V and P-V curves agree extremely well with the measured data. However, it means that the resistance values should not be used alone to make strong diagnostic claims about contact degradation, leakage pathways, soldering defects, or ageing mechanisms. The main practical implication is that the extracted SDM can be used confidently as a high-fidelity STC reference model for the investigated PV module. It can support module-level simulation, maximum-power prediction, MPPT algorithm testing, and comparison between measured and expected I-V curves. Because the model reproduces both the I-V and P-V curves with very small errors, it can also serve as a baseline for future studies involving degradation, fault detection, or performance comparison. Nevertheless, the model should not be interpreted as a complete outdoor performance model. The parameter set was extracted from a single I-V curve measured at STC. Therefore, the robustness of the extraction procedure across different modules, datasets, irradiance levels, and temperatures has not been established in the present study. Outdoor operation involves variations in irradiance, cell temperature, wind speed, spectrum, soiling, humidity, and ageing. Therefore, annual energy-yield prediction or field-performance simulation

would require additional translation equations or multi-condition parameter extraction using I-V curves measured at different irradiance and temperature levels.

Future work should therefore extend the present full-curve extraction framework to multiple operating conditions. Fitting several I-V curves simultaneously would make it possible to evaluate how I_{ph}, I_0, R_{sh}, and a change with irradiance and temperature. In addition, uncertainty analysis, sensitivity analysis, and confidence-interval estimation should be included to determine which parameters are strongly identifiable and which are only weakly constrained by the available data. Such extensions would improve the physical interpretation of the extracted parameters and strengthen the model's use for diagnostics and long-term PV performance prediction. Overall, the results confirm that the proposed full-curve extraction method is highly effective for reconstructing the measured STC behaviour of the commercial PV module. At the same time, they show that numerical accuracy and physical identifiability are not identical. The extracted model is therefore most reliable as an accurate STC curve-reconstruction tool, while broader physical diagnosis and outdoor prediction require additional measurements, uncertainty analysis, and multi-condition validation.

4. Conclusion

This study developed and demonstrated a full-curve five-parameter extraction method for a commercial PV module using the single-diode model at STC. By fitting all 100 measured voltage-current points, the proposed approach accurately reconstructed the measured I-V and P-V characteristics over the entire operating range. The model achieved a maximum-power error of only 0.009% together with near-unity agreement between the measured and reconstructed curves. These results confirm that residual-based full-curve fitting provides an accurate and reproducible approach for extracting SDM parameters from measured PV module I-V data.

The key methodological conclusion is that full-curve fitting offers stronger validation than characteristic-point-only extraction because it evaluates the model over the entire operating range. The key interpretive conclusion is that excellent numerical agreement should be accompanied by parameter-plausibility assessment, especially when the measured curve is rounded or nearly ideal before the knee region. Future work should apply the method to multiple irradiance and temperature levels, compare deterministic fitting with metaheuristic and hybrid approaches, and include measurement-uncertainty analysis.

Declarations

Author contributions. The whole of the work is Erdem Cuce's: the conception and design of the study, the analysis and interpretation of the results, and the writing of the manuscript.

Conflicts of interest. The authors declare no competing interests.

Data availability. The data that support the findings of this study are available from the corresponding author upon reasonable request.

References

Abbassi, Rabeh; Abbassi, Abdelkader; Jemli, Mohamed; Chebbi, Souad (2018) 'Identification of unknown parameters of solar cell models: A comprehensive overview of available approaches', *Renewable and Sustainable Energy Reviews*, 90, pp. 453-474. Available at: https://doi.org/10.1016/j.rser.2018.03.011

Abdirahman, Abdinasir Ahmed; Asif, Muhammad; Cuce, Erdem; Ahmed, Ijaz; Alqahtani, Mohammed; Khalid, Muhammad (2025) 'Optimizing PV systems in high-temperature environments: A SWOT-based analysis of cooling technologies', *Energy Strategy Reviews*, 61, pp. 101828. Available at: https://doi.org/10.1016/j.esr.2025.101828

Abdulrazzaq, Ali Kareem; Bognár, György; Plesz, Balázs (2022) 'Accurate method for PV solar cells and modules parameters extraction using I–V curves', *Journal of King Saud University - Engineering Sciences*, 34(1), pp. 46-56. Available at: https://doi.org/10.1016/j.jksues.2020.07.008

Abdulrazzaq, Ali Kareem; Bognár, György; Plesz, Balázs (2025) 'Enhanced single-diode model parameter extraction method for photovoltaic cells and modules based on integrating genetic algorithm, particle swarm optimization, and comparative objective functions', *Journal of Computational Electronics*, 24(2). Available at: https://doi.org/10.1007/s10825-025-02282-w

Angelova, Dorotea Dimitrova; Fernández, Diego Carmona; Godoy, Manuel Calderón; Moreno, Juan Antonio Álvarez; González, Juan Félix González (2024) 'A Review on Digital Twins and Its Application in the Modeling of Photovoltaic Installations', *Energies*, 17(5), pp. 1227. Available at: https://doi.org/10.3390/en17051227

Batzelis, Efstratios I.; Papathanassiou, Stavros A. (2016) 'A Method for the Analytical Extraction of the Single-Diode PV Model Parameters', *IEEE Transactions on Sustainable Energy*, 7(2), pp. 504-512. Available at: https://doi.org/10.1109/tste.2015.2503435

Ćalasan, M., Abdel Aleem, S.H.E. and Zobaa, A.F (2020) 'On the root mean square error calculation for parameter estimation of photovoltaic models: A critical review', *Energy Conversion and Management*.

Carrillo, José Manuel; Martínez-Moreno, Francisco; Lorenzo, Celena; Lorenzo, Eduardo (2017) 'Uncertainties on the outdoor characterization of PV modules and the calibration of reference modules', *Solar Energy*, 155, pp. 880-892. Available at: https://doi.org/10.1016/j.solener.2017.07.028

Cubas, Javier; Pindado, Santiago; De Manuel, Carlos (2014) 'Explicit Expressions for Solar Panel Equivalent Circuit Parameters Based on Analytical Formulation and the Lambert W-Function', *Energies*, 7(7), pp. 4098-4115. Available at: https://doi.org/10.3390/en7074098

Cuce, E. and Bali, T (2009) 'Variation of cell parameters of a p-Si PV cell with different solar irradiances and cell temperatures in humid climates', *Fourth International Energy*.

Cuce, Erdem; Cuce, Pinar Mert; Karakas, Ibrahim Hakki; Bali, Tulin (2017) 'An accurate model for photovoltaic (PV) modules to determine electrical characteristics and thermodynamic performance parameters', *Energy Conversion and Management*, 146, pp. 205-216. Available at: https://doi.org/10.1016/j.enconman.2017.05.022

De Soto, W.; Klein, S.A.; Beckman, W.A. (2006) 'Improvement and validation of a model for photovoltaic array performance', *Solar Energy*, 80(1), pp. 78-88. Available at: https://doi.org/10.1016/j.solener.2005.06.010

Deotti, Lucas Meirelles Pires; da Silva, Ivo Chaves (2023) 'A survey on the parameter extraction problem of the photovoltaic single diode model from a current–voltage curve', *Solar Energy*, 263, pp. 111930. Available at: https://doi.org/10.1016/j.solener.2023.111930

F. Holmgren, William; W. Hansen, Clifford; A. Mikofski, Mark (2018) 'pvlib python: a python package for modeling solar energy systems', *Journal of Open Source Software*, 3(29), pp. 884. Available at: https://doi.org/10.21105/joss.00884

Gnetchejo, Patrick Juvet; Ndjakomo Essiane, Salomé; Ele, Pierre; Wamkeue, René; Mbadjoun Wapet, Daniel; Perabi Ngoffe, Steve (2019) 'Important notes on parameter estimation of solar photovoltaic cell', *Energy Conversion and Management*, 197, pp. 111870. Available at: https://doi.org/10.1016/j.enconman.2019.111870

Gopi, Ajith; Sudhakar, K.; Ngui, W.K.; Kirpichnikova, I.M.; Cuce, Erdem (2021) 'Energy analysis of utility-scale PV plant in the rain-dominated tropical monsoon climates', *Case Studies in Thermal Engineering*, 26, pp. 101123. Available at: https://doi.org/10.1016/j.csite.2021.101123

Gu, Zaiyu; Xiong, Guojiang; Fu, Xiaofan (2023) 'Parameter Extraction of Solar Photovoltaic Cell and Module Models with Metaheuristic Algorithms: A Review', *Sustainability*, 15(4), pp. 3312. Available at: https://doi.org/10.3390/su15043312

Inbamani, Abinaya; Prabha, S. U. (2023) 'Predicting the Single Diode Model Parameters using Machine Learning Model', *Electric Power Components and Systems*, 51(14), pp. 1385-1397. Available at: https://doi.org/10.1080/15325008.2023.2199737

Izci, Davut; Ekinci, Serdar; Hussien, Abdelazim G. (2024) 'Efficient parameter extraction of photovoltaic models with a novel enhanced prairie dog optimization algorithm', *Scientific Reports*, 14(1). Available at: https://doi.org/10.1038/s41598-024-58503-y

Jain, A (2004) 'Exact analytical solutions of the parameters of real solar cells using Lambert W-function', *Solar Energy Materials and Solar Cells*, 81(2), pp. 269-277. Available at: https://doi.org/10.1016/j.solmat.2003.11.018

Li, Shuijia; Gong, Wenyin; Gu, Qiong (2021) 'A comprehensive survey on meta-heuristic algorithms for parameter extraction of photovoltaic models', *Renewable and Sustainable Energy Reviews*, 141, pp. 110828. Available at: https://doi.org/10.1016/j.rser.2021.110828

Lidaighbi, Souad; Elyaqouti, Mustapha; Ben Hmamou, Dris; Saadaoui, Driss; Assalaou, Khalid; Arjdal, Elhanafi (2022) 'A new hybrid method to estimate the single-diode model parameters of solar photovoltaic panel', *Energy Conversion and Management: X*, 15, pp. 100234. Available at: https://doi.org/10.1016/j.ecmx.2022.100234

Lineykin, Simon; Averbukh, Moshe; Kuperman, Alon (2014) 'An improved approach to extract the single-diode equivalent circuit parameters of a photovoltaic cell/panel', *Renewable and Sustainable Energy Reviews*, 30, pp. 282-289. Available at: https://doi.org/10.1016/j.rser.2013.10.015

Ma, Xin; Ghosh, Aritra; Cuce, Erdem; Saboor, Shaik (2024) 'Building integrated photovoltaic-thermal systems (BIPVT) and spectral splitting technology: A critical review', *Next Sustainability*, 4, pp. 100056. Available at: https://doi.org/10.1016/j.nxsust.2024.100056

Mermoud, A. and Lejeune, T (2010) 'Performance assessment of a simulation model for PV modules of any available technology', *Proceedings of the 25th European Photovoltaic Solar Energy Conference and Exhibit*, pp. 4786–4791.

Nunes, H.G.G.; Pombo, J.A.N.; Mariano, S.J.P.S.; Calado, M.R.A.; Felippe de Souza, J.A.M. (2018) 'A new high performance method for determining the parameters of PV cells and modules based on guaranteed convergence particle swarm optimization', *Applied Energy*, 211, pp. 774-791. Available at: https://doi.org/10.1016/j.apenergy.2017.11.078

Qin, Cheng; Li, Jianing; Yang, Chen; Ai, Bin; Zhou, Yecheng (2024) 'Comparative Study of Parameter Extraction from a Solar Cell or a Photovoltaic Module by Combining Metaheuristic Algorithms with Different Simulation Current Calculation Methods', *Energies*, 17(10), pp. 2284. Available at: https://doi.org/10.3390/en17102284

Santos, Leticia de Oliveira; AlSkaif, Tarek; Barroso, Giovanni Cordeiro; Carvalho, Paulo Cesar Marques de (2024) 'Photovoltaic power estimation and forecast models integrating physics and machine learning: A review on hybrid techniques', *Solar Energy*, 284, pp. 113044. Available at: https://doi.org/10.1016/j.solener.2024.113044

Song, Zhaoxu; Fang, Kun; Sun, Xiaofang; Liang, Ying; Lin, Wei; Xu, Chuanzhong; Huang, Gongyi; Yu, Fei (2021) 'An Effective Method to Accurately Extract the Parameters of Single Diode Model of Solar Cells', *Nanomaterials*, 11(10), pp. 2615. Available at: https://doi.org/10.3390/nano11102615

Soudagar, Manzoore Elahi M; Ramesh, S; Khan, T M Yunus; Almakayeel, Naif; Ramesh, R; Ghazali, Nik Nazri Nik; Cuce, Erdem; Shelare, Sagar (2024) 'An overview of the existing and future state of the art advancement of hybrid energy systems based on PV-solar and wind', *International Journal of Low-Carbon Technologies*, 19, pp. 207-216. Available at: https://doi.org/10.1093/ijlct/ctad123

Sreenath, S.; Sudhakar, K.; Yusop, A.F.; Cuce, Erdem; Solomin, Evgeny (2020) 'Analysis of solar PV glare in airport environment: Potential solutions', *Results in Engineering*, 5, pp. 100079. Available at: https://doi.org/10.1016/j.rineng.2019.100079

Tamrakar, Vivek; S.C, Gupta; Sawle, Yashwant (2015) 'Single-Diode Pv Cell Modeling And Study Of Characteristics Of Single And Two-Diode Equivalent Circuit', *Electrical and Electronics Engineering: An International Journal*, 4(3), pp. 13-24. Available at: https://doi.org/10.14810/elelij.2015.4302

Villalva, M.G.; Gazoli, J.R.; Filho, E.R. (2009) 'Comprehensive Approach to Modeling and Simulation of Photovoltaic Arrays', *IEEE Transactions on Power Electronics*, 24(5), pp. 1198-1208. Available at: https://doi.org/10.1109/tpel.2009.2013862

Xu, Jie; Zhou, Chuxiang; Li, Wei (2023) 'Photovoltaic single diode model parameter extraction by dI/dV-assisted deterministic method', *Solar Energy*, 251, pp. 30-38. Available at: https://doi.org/10.1016/j.solener.2023.01.009

Xu, Jie; Liu, Jinfeng; Zhu, Chen; Chen, Qingyun; Zhang, Yi (2025) 'Parameter estimation of photovoltaic single-diode model using an integral form and hybrid objective function', *Solar Energy*, 300, pp. 113820. Available at: https://doi.org/10.1016/j.solener.2025.113820

Younis, Abubaker; Bakhit, Abdalaziz; Onsa, Mahmoud; Hashim, Mohsin (2022) 'A comprehensive and critical review of bio-inspired metaheuristic frameworks for extracting parameters of solar cell single and double diode models', *Energy Reports*, 8, pp. 7085-7106. Available at: https://doi.org/10.1016/j.egyr.2022.05.160

HOW TO CITE THIS ARTICLE

Cuce, E. (2026). Full-Curve Five-Parameter Extraction of a Commercial Photovoltaic Module Using the Single-Diode Model at Standard Test Conditions. *Energy Catalyst*, 2, 269-288. https://doi.org/10.65582/ec.2026.011

COPYRIGHT AND LICENCE

© 2026 The Author(s). This is an open access article distributed under the terms of the Creative Commons Attribution (CC BY 4.0) licence, which permits unrestricted use, distribution and reproduction in any medium, provided the original work is properly cited.